Application of Remote Sensing in Environmental Monitoring and Public Health

Presented by Fahimeh Youssefi

20-22 June 2022
National Cartographic Center (NCC) – Tehran, Iran

In the name of God

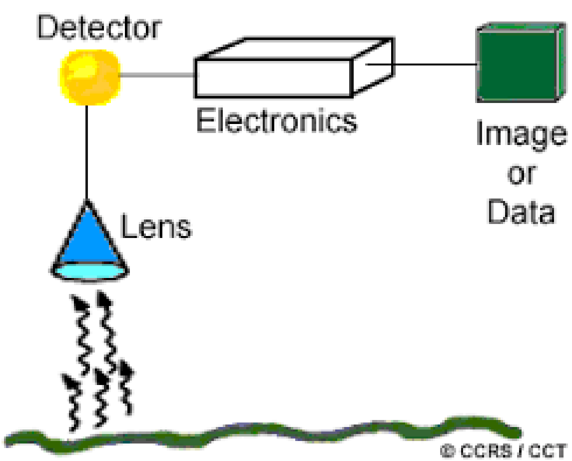
Content

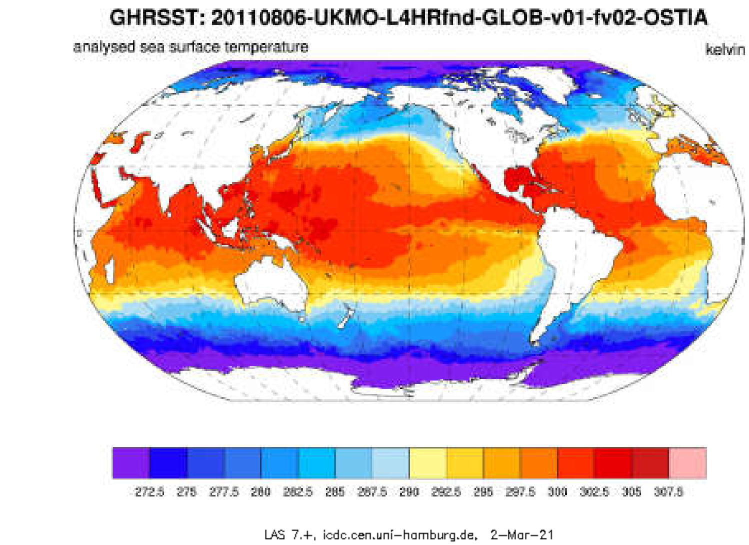
- Introduce the capability of remote sensing data in estimating environmental parameters
- Monitoring climate change and its impact on public health
- Environmental parameters and vector-borne diseases
- Time series analysis of remote sensing data in temporal and spatial prediction of vector-borne disease
- Utilization of early warning system in public health management

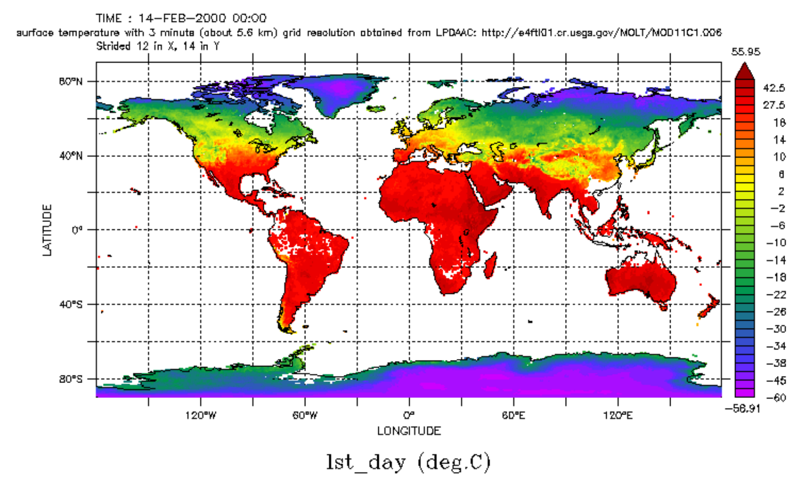
Estimating Environmental Parameters Using RS Data

- Temperature
- Evapotranspiration (ET)
- Soil Moisture
- Air Pollutions
- Precipitation
- Drought Indices
- Vegetation Indices

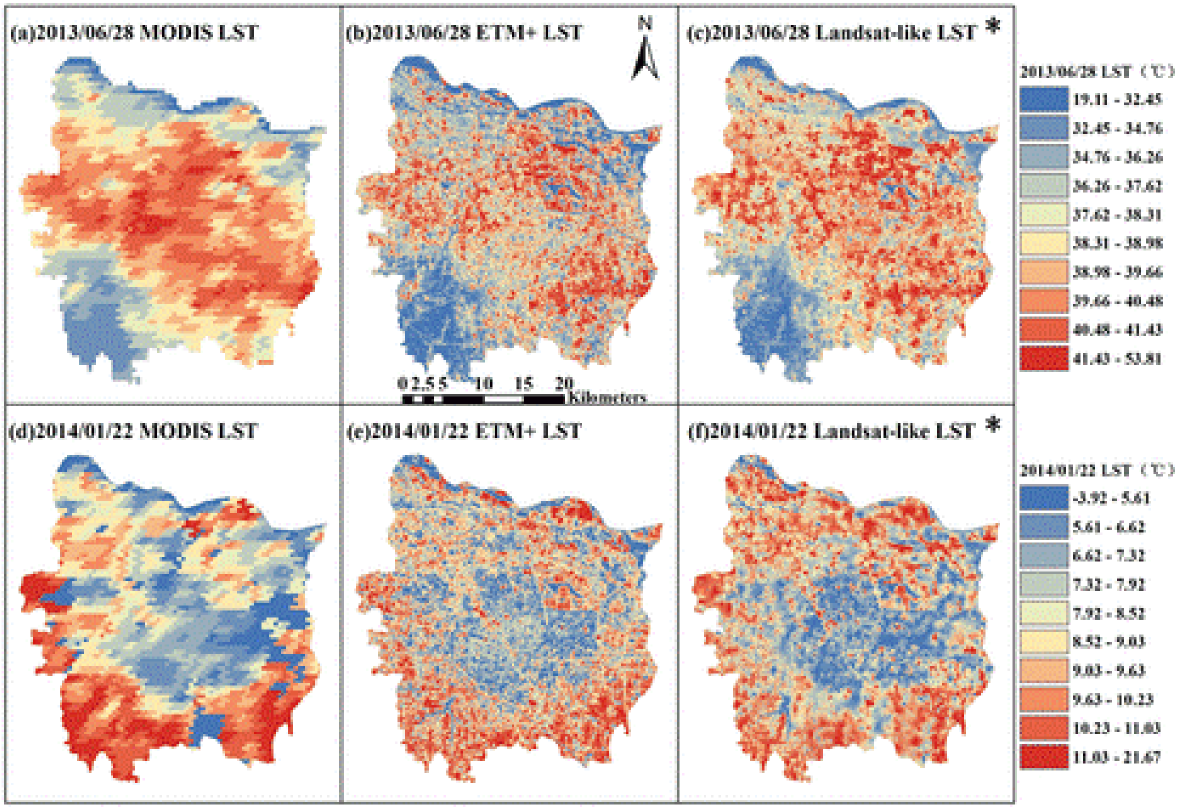
Temperature



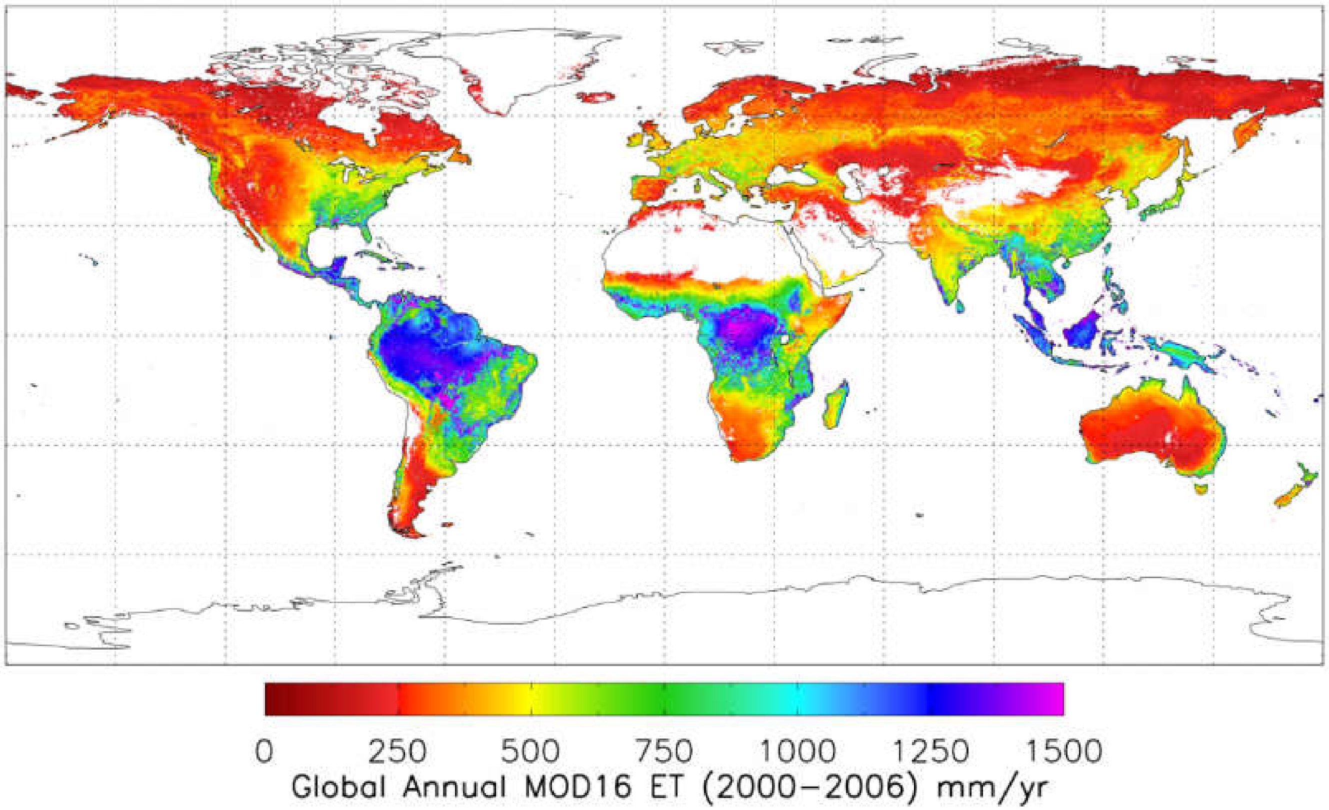




Temperature

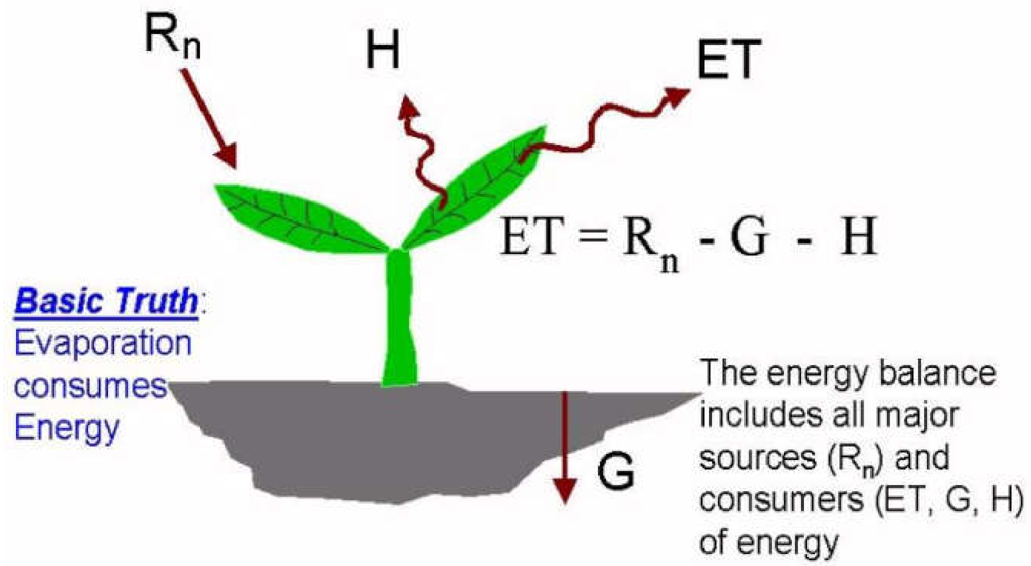


Evapotranspiration (ET)

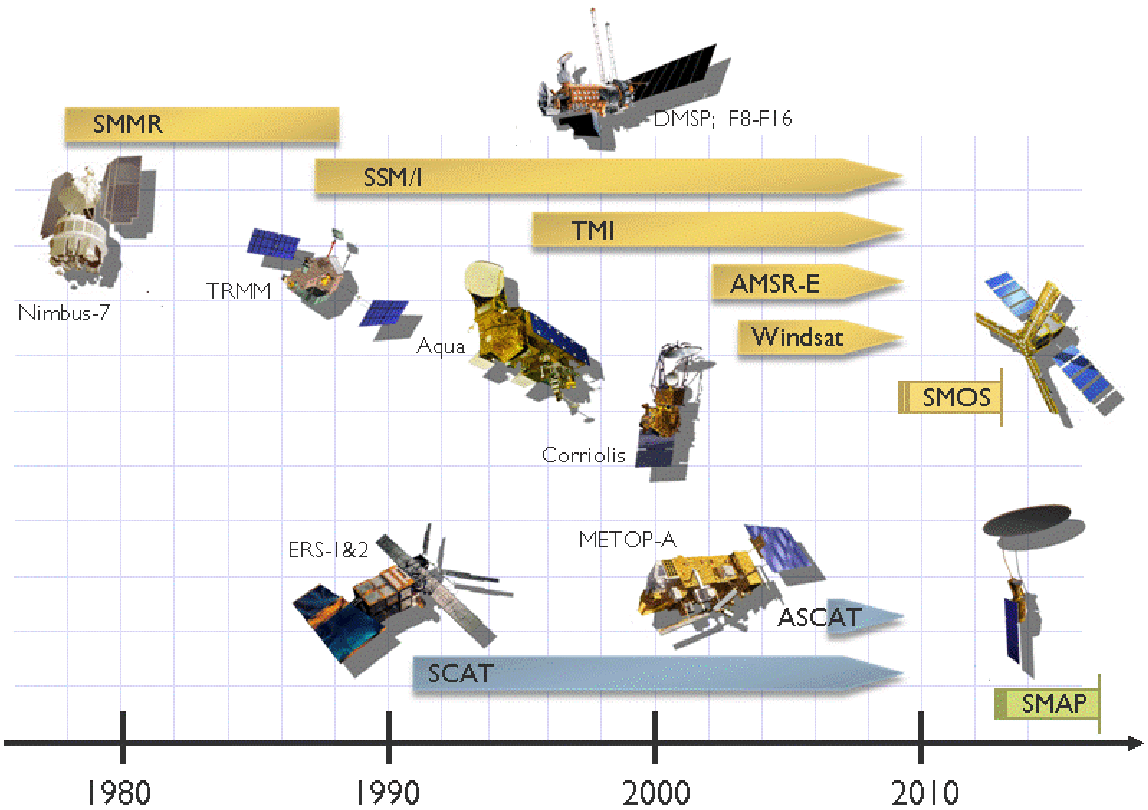


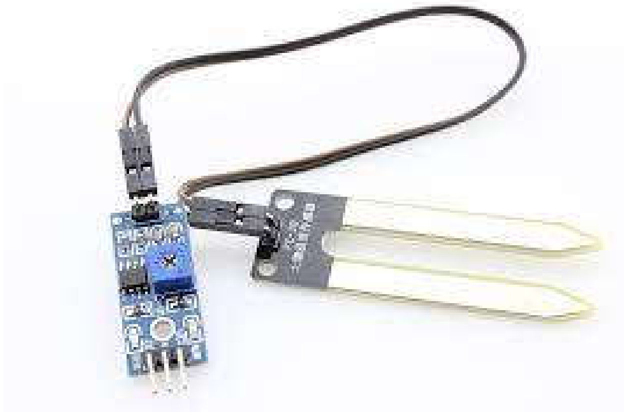
Common methods to estimate ET

- SEBAL
- SEBS
- METRIC



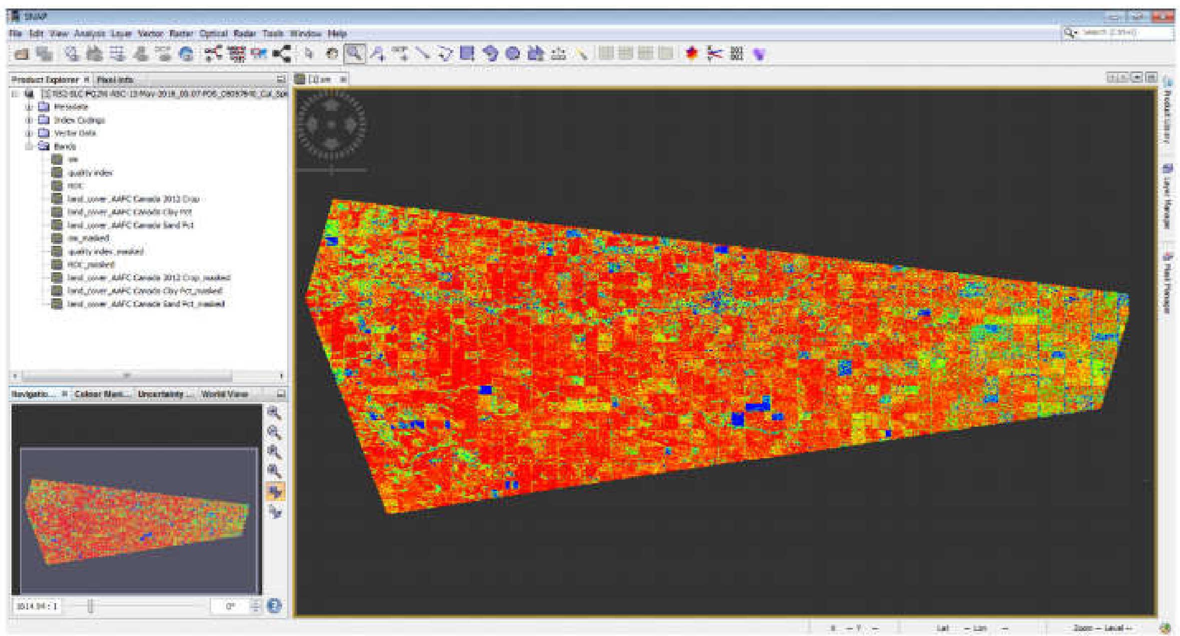
Soil Moisture





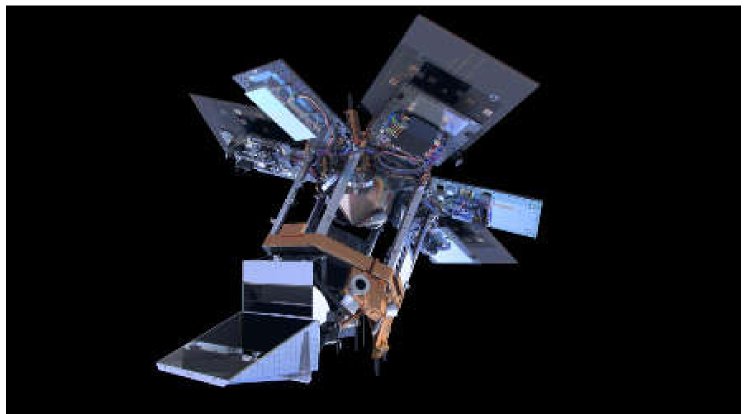
Soil Moisture

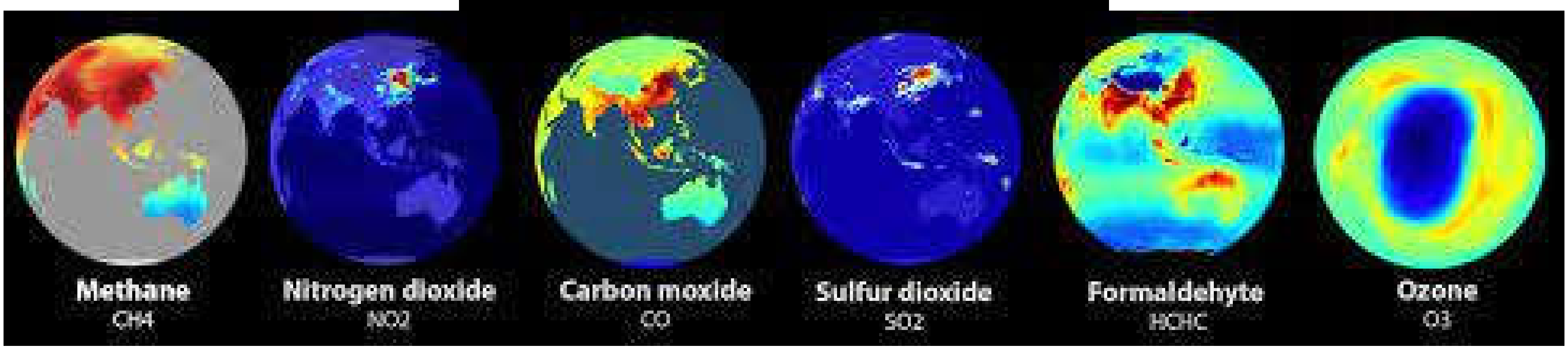
Soil Moisture Processing with the Soil Moisture Toolbox in the SNAP Software Using RADARSAT-2 Data



Air Pollutions

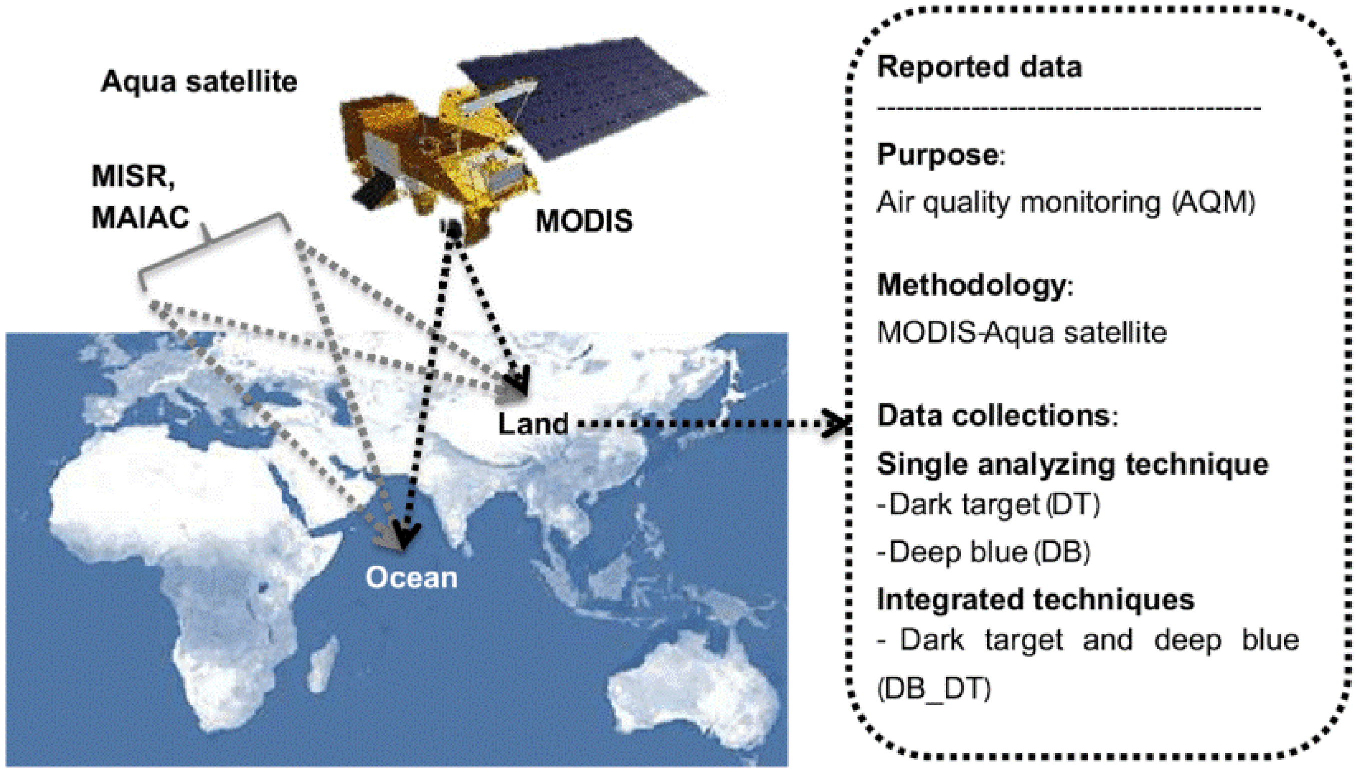
Sentinel-5p





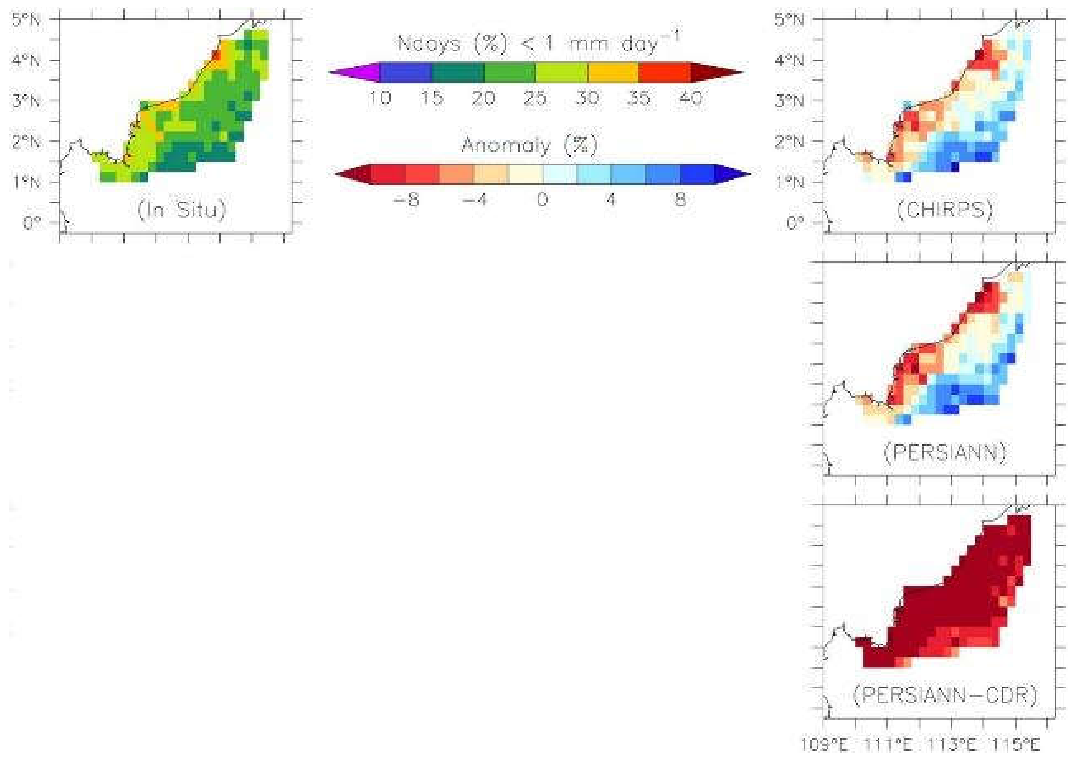
Air Pollutions

MODIS

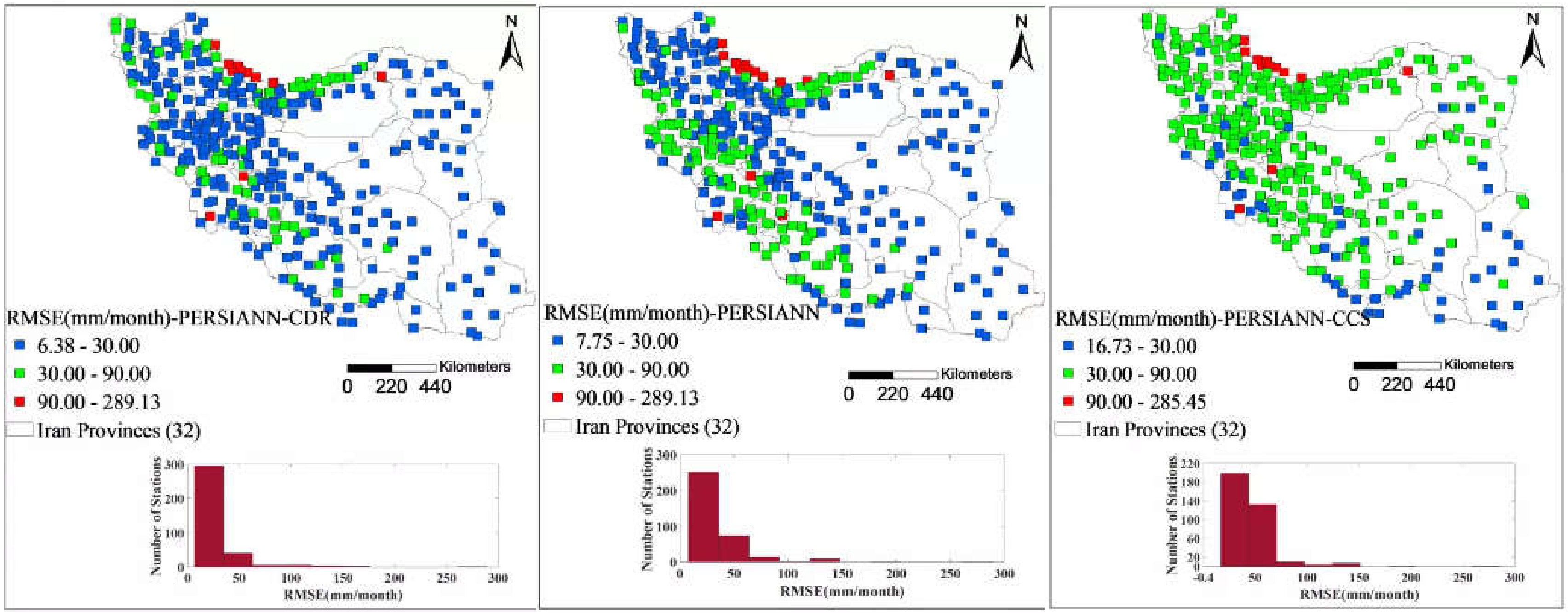


Precipitation

- PERSIANN, PERSIANN-CDR, PERSIANN
- TRMM
- CHIRPS
- SM2RAIn-ASCAT



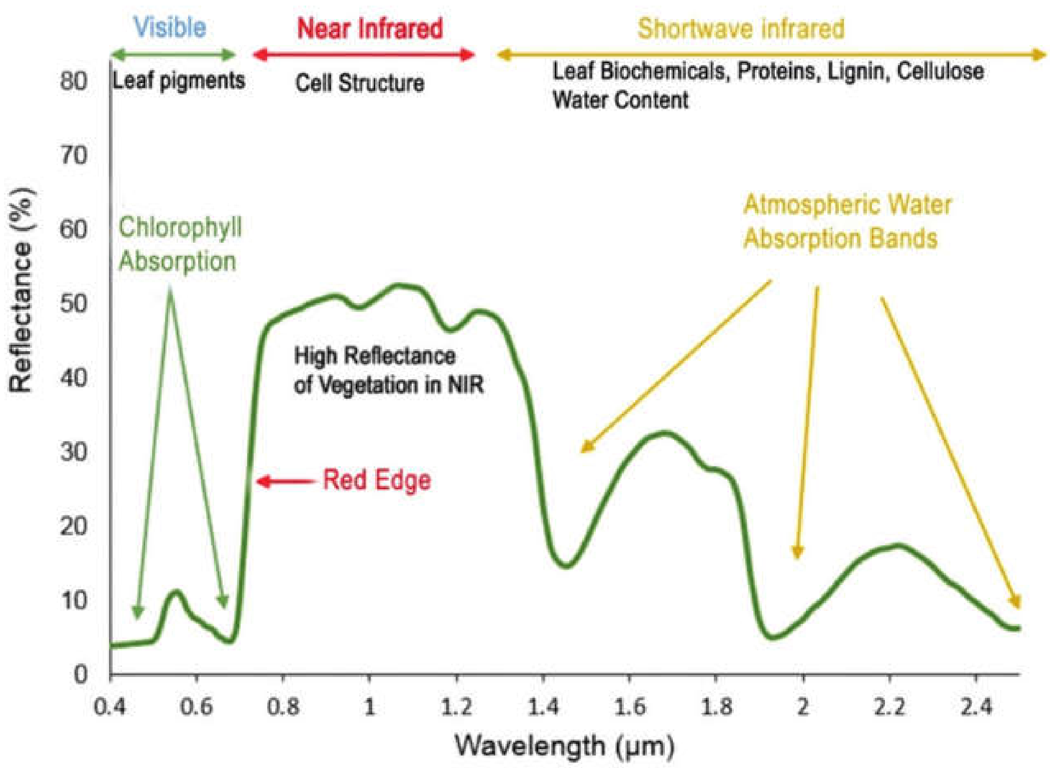
Precipitation



Drought Indices

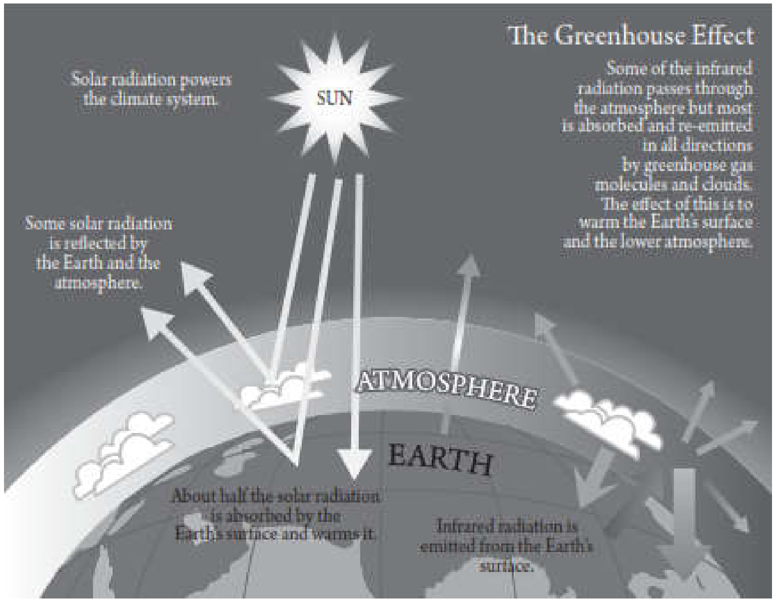
Index	Type of drought
1. Normalized Difference Vegetation Index (NDVI)	Agricultural
2. Deviation $_{NDVI}$ Index	Agricultural
3. Enhanced Vegetation Index (EVI)	Agricultural
4. Vegetation Condition Index (VCI)	Agricultural
5. Monthly Vegetation Condition Index	Agricultural
6. Temperature Condition Index (TCI)	Agricultural
7. Vegetation Health Index (VHI)	Agricultural
8. Normalised Difference Temperature Index (NDTI)	Agricultural
9. Crop Water Stress Index (SWSI)	Hydrological
10. Drought Severity Index (DSI)	Hydrological
11. Temperature-Vegetation Dryness Index (TVDI)	Agricultural
12. Normalized Difference Water Index (NDWI)	Hydrological
13. Reconnaissance Drought Index (RDI)	Hydrological

Vegetation Indices



Indices	Equation
NDVI	$\frac{NIR - Red}{NIR + Red}$
GNDVI	$\frac{NIR - Green}{NIR + Green}$
$NDVI_{ededge}$	$\frac{NIR - Rededge}{NIR + Rededge}$
SR	$\frac{NIR}{Red}$
CI_{green}	$\frac{NIR}{Green} - 1$
$CI_{rededge}$	$\frac{NIR}{Rededge} - 1$

Climate Change



- Rising temperatures
- Melting ice and snow
- Drought
- Rising sea levels
- Changing rainfall pattern
- Rising levels of CO_2, methane, and other greenhouse gases
- Severe storms
- Increased intense tropical cyclone activity

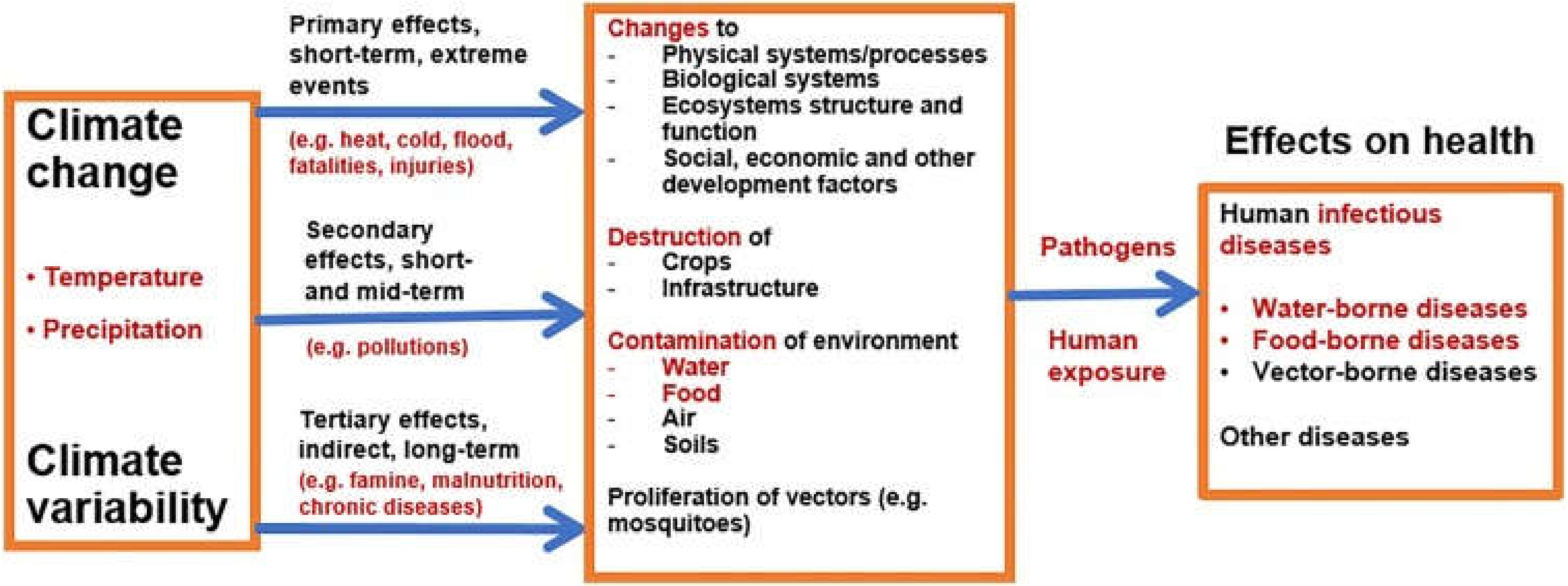
Causes of Climate Change

- Adverse Health Consequences
- Vulnerable Population
  - Areas with a high baseline prevalence of climate-sensitive diseases, such as malaria
  - Areas where epidemic disease is associated with climate patterns, such as cholera and other diseases linked to the El -Niño Southern Oscillation
  - Areas with reduced access to food or water as a result of drought or other impacts of climate change
  - Areas of increased risk of water-borne or vector-borne disease.

Causes of Climate Change

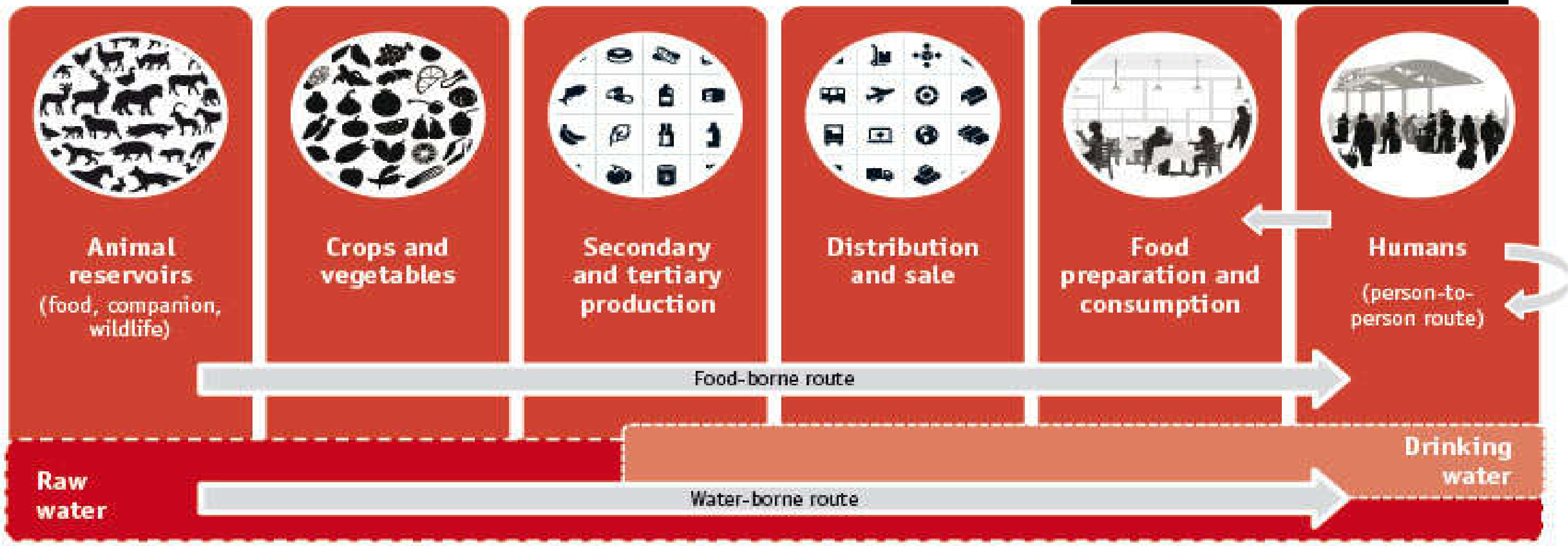
- Effects on Biological Systems
  - Changes in the lifecycles of vectors, reservoirs, and pathogens
  - Impacts on diseases of wildlife and plants
  - Disruptions of the interactions among species
  - Destruction of habitats.
- Effects on Social Systems
  - Droughts, floods, and sea level rise often force people to flee their homes and communities in search of safer places with better economic opportunities
  - Food insecurity and resultant food price shocks are often associated with violence and other forms of conflict

Climate Change and Public Health



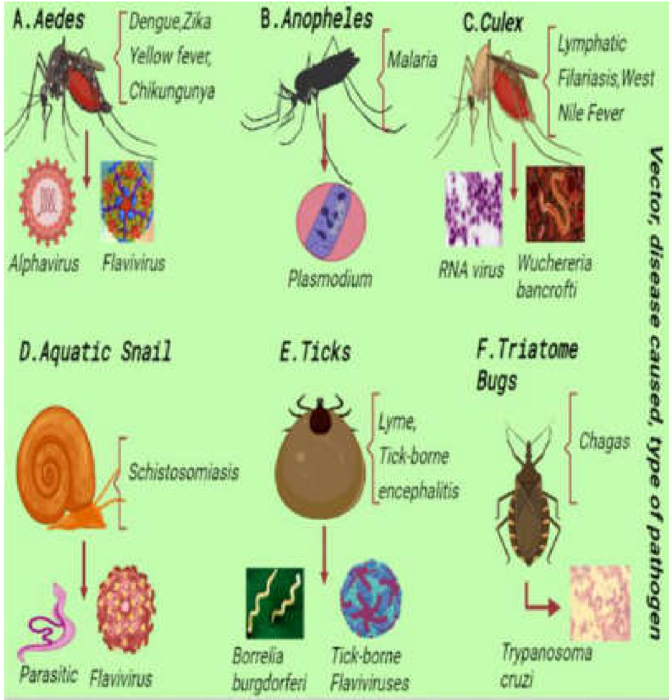
Climate Change and Public Health

- Vector-Borne Disease
- Water-Borne Disease
- Food-Borne Disease



Vector-Borne Disease

- Vector-borne diseases are caused by pathogens that are carried or transmitted by invertebrates, mostly arthropods.



  - Malaria
  - Leishmaniasis
  - Yellow fever
  - Dengue and severe dengue
  - …

Water-Borne and Food-Borne Disease

- Floods and droughts impact agricultural systems and the availability and safety of food and water.
- Agriculture, the sector that uses the most water, accounts for much water pollution. Water carries waste from people and animals, contributing to agricultural runoff, and, once contaminated, provides many opportunities and pathways for people to acquire waterborne or foodborne disease.
- Rainfall has been linked to gastrointestinal illness and to waterborne disease in both high-income and low-income countries.

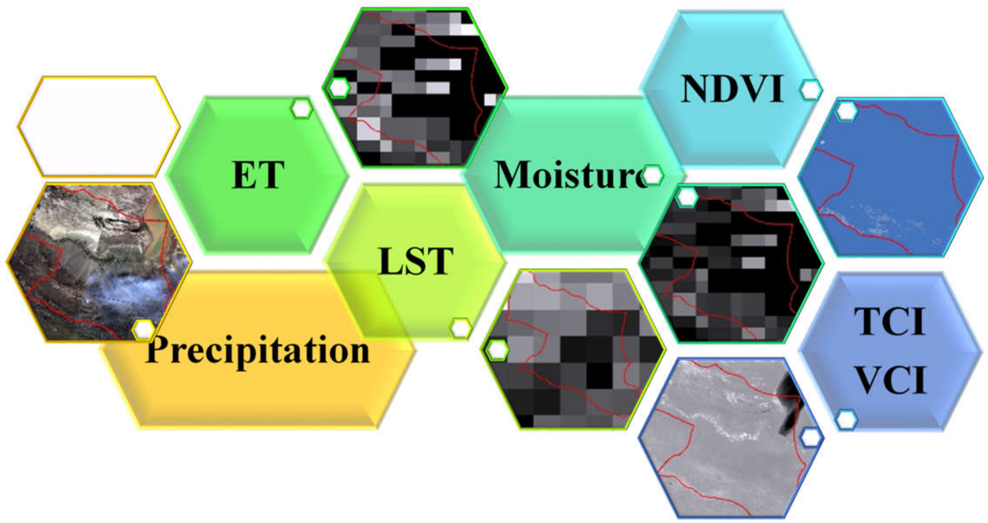
Water-Born and Food-Borne Disease

Climate factors have been associated with the following:

- Bacteria, such as pathogenic E. coli and species of Campylobacter, Leptospira, Salmonella, and Vibrio.
- Parasites, such as species of Cryptosporidium, Cyclospora, Giardia, and Toxoplasma
- Viruses, such as hepatitis A and E viruses, norovirus, and polioviru

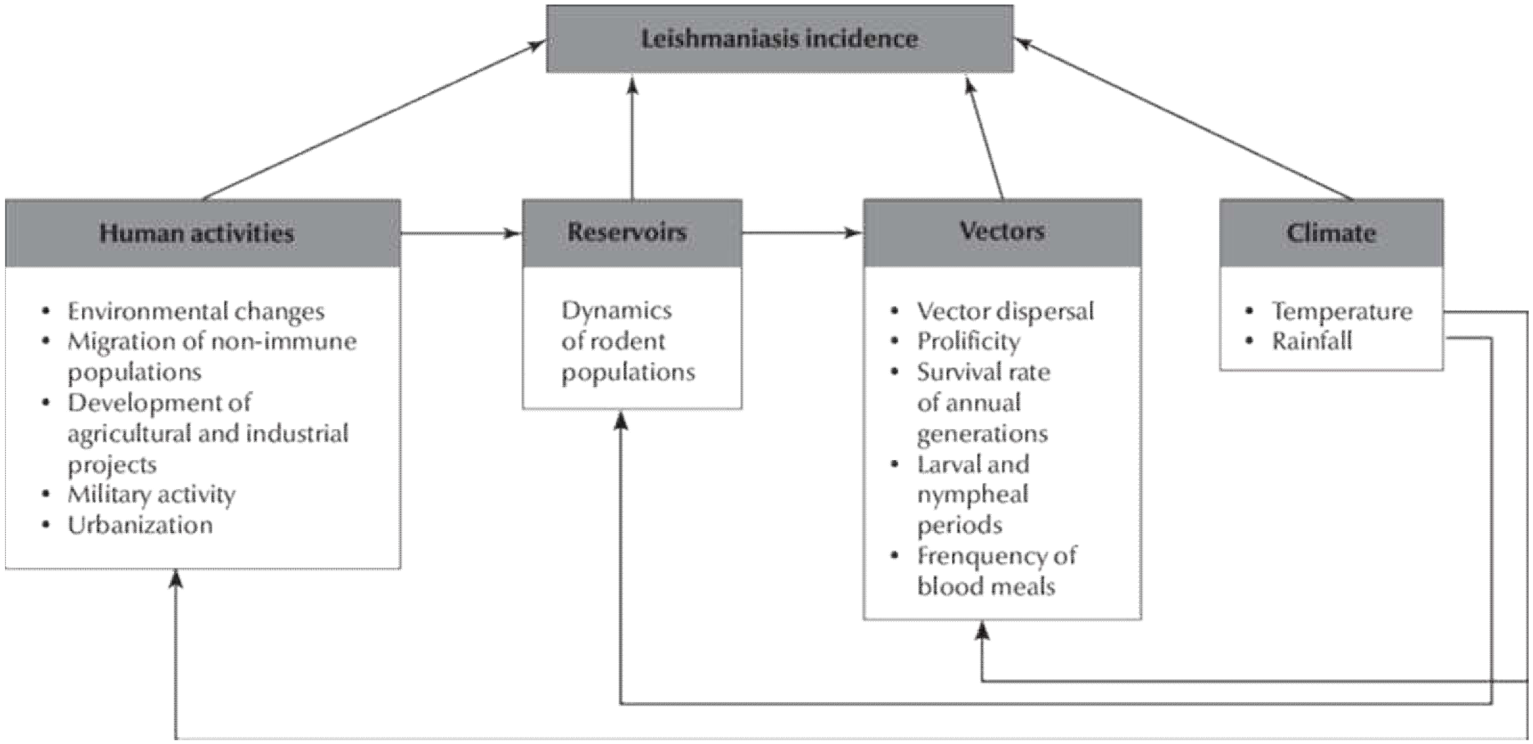
Environmental parameters and vector-borne diseases

Malaria



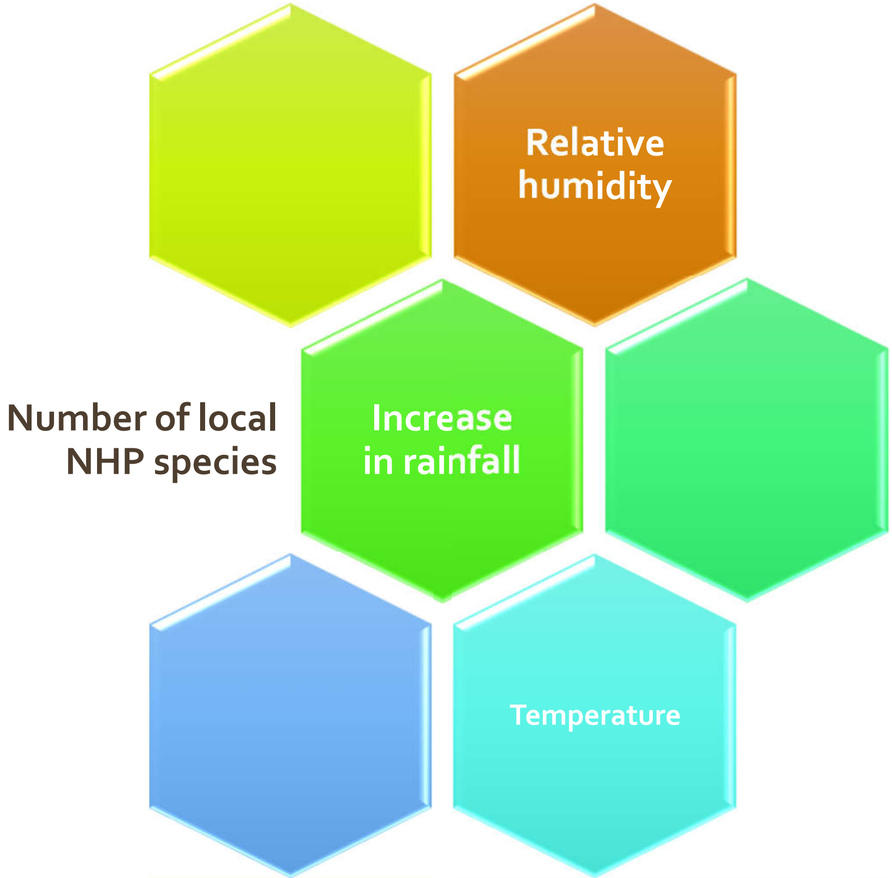
Environmental parameters and vector-borne diseases

Leishmaniasis



Environmental parameters and vector-borne diseases

Yellow Fever

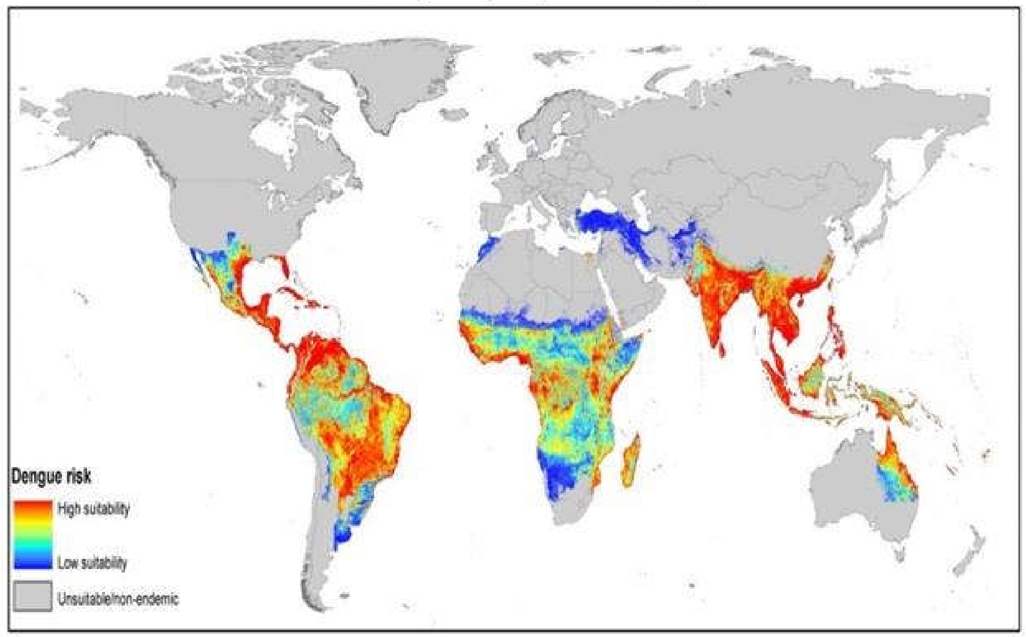


Environmental parameters and vector-borne diseases

Dengue

- **Precipitation**
- **Temperature**

Distribution of global dengue risk (Simmons CP et al, 2012)



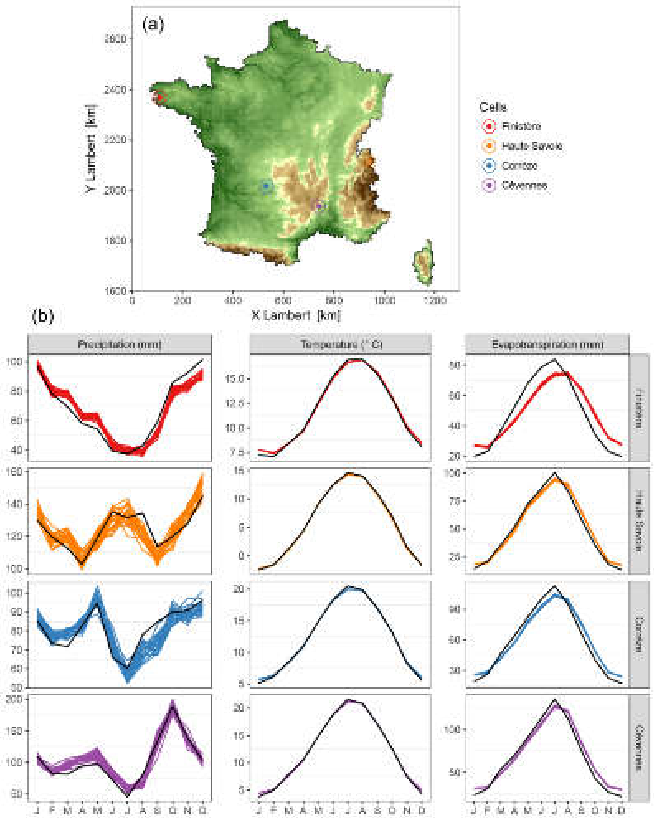
Time series analysis of remote sensing data in temporal and spatial prediction of vector-borne disease

Spatial

- **Risk map**

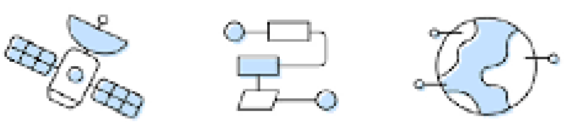
Temporal

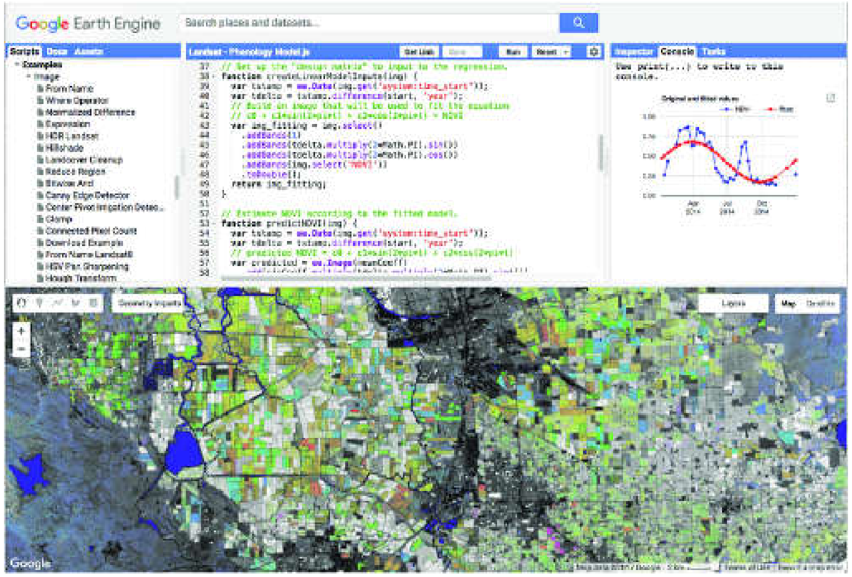
- **Seasonal Risk**



Google Earth Engine Cloud-Based Platform

- Google Earth Engine (GEE) has rendered it possible to analyze time series remote sensing data easily and in the shortest time by providing fast and accessible processing space and easy access to free remote sensing data.





Sample of Temporal Prediction

sensors

MDPI

Article

Temporal Monitoring and Predicting of the Abundance of Malaria Vectors Using Time Series Analysis of Remote Sensing Data through Google Earth Engine

Fahimeh Youssefi [1,*], Mohammad Javad Valadan Zoej [1], Ahmad Ali Hanafi-Bojd [2], Alireza Borhani Dariane [3], Mehdi Khaki [4], Alireza Safdarinezhad [5] and Ebrahim Ghaderpour [6]

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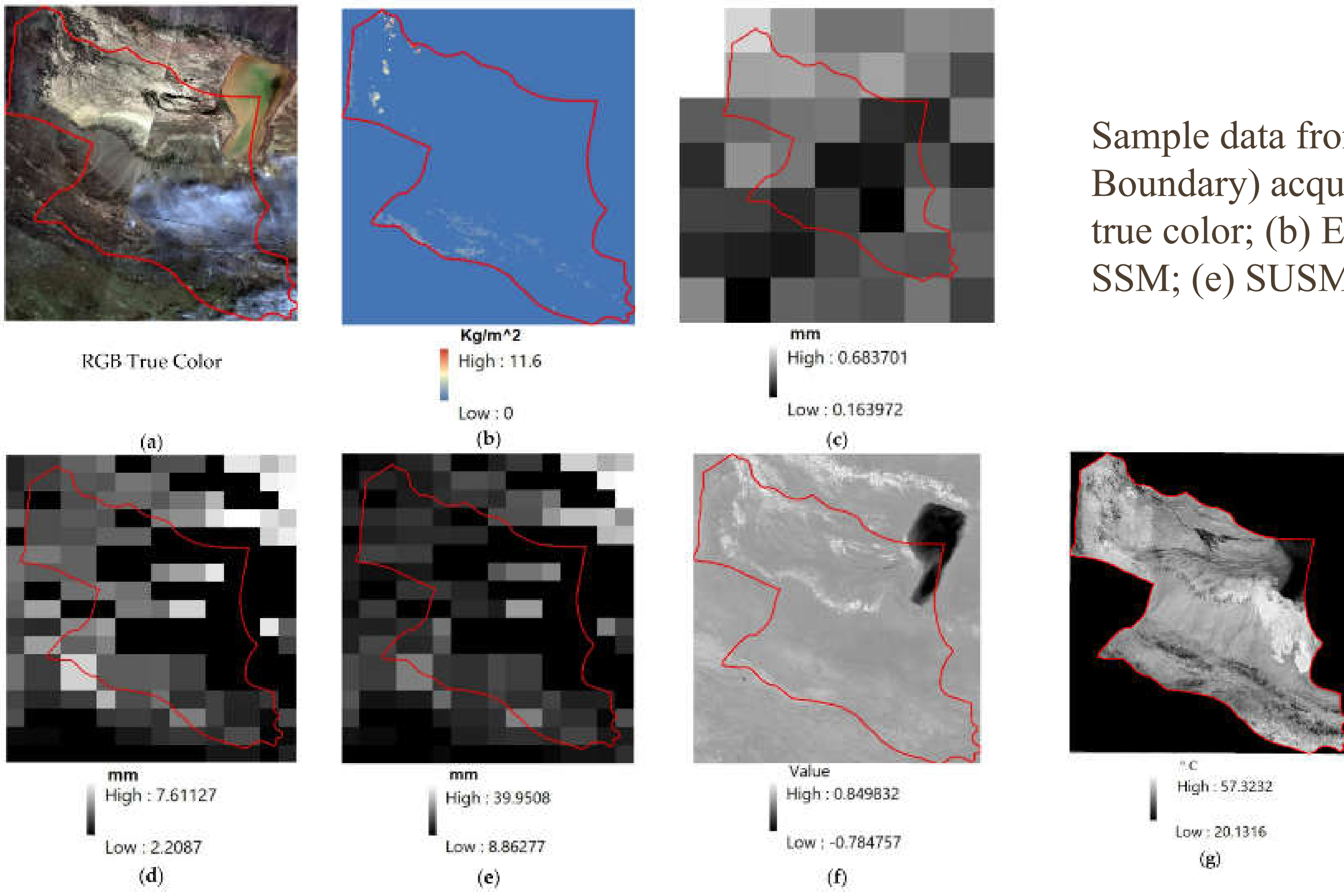
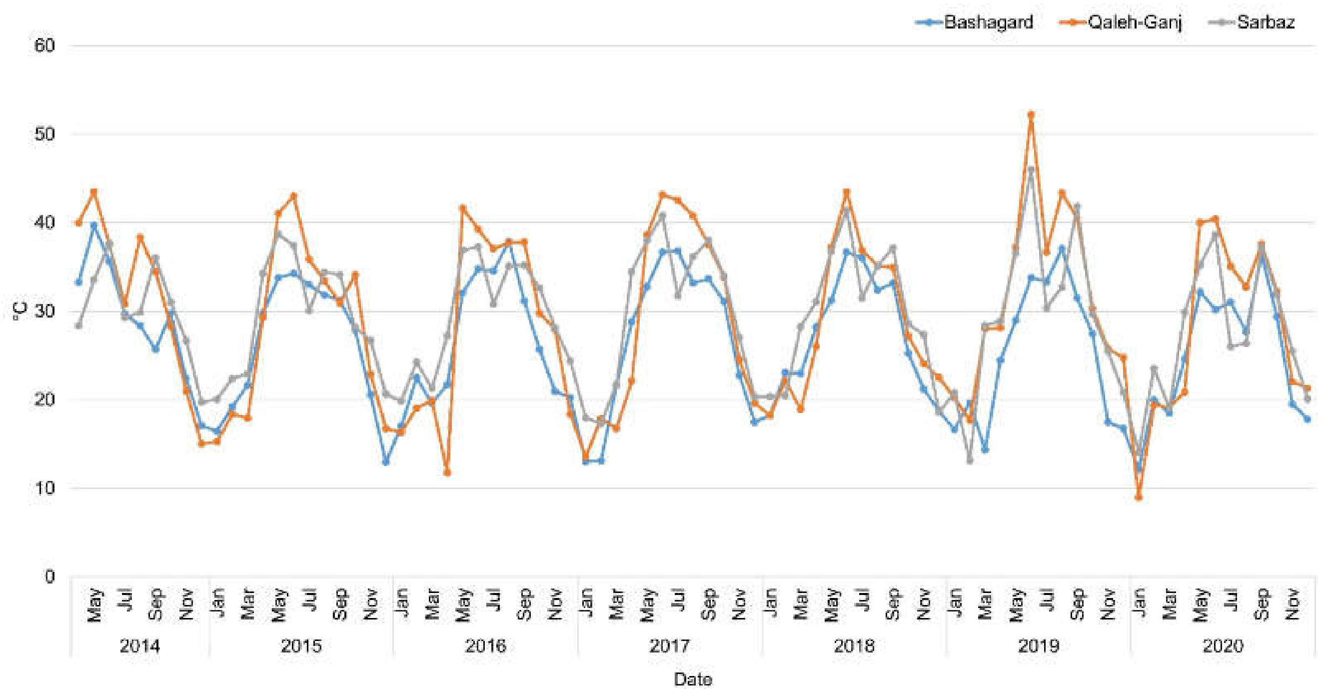
* Correspondence: youssefi@email.kntu.ac.ir

Sample of Temporal Prediction

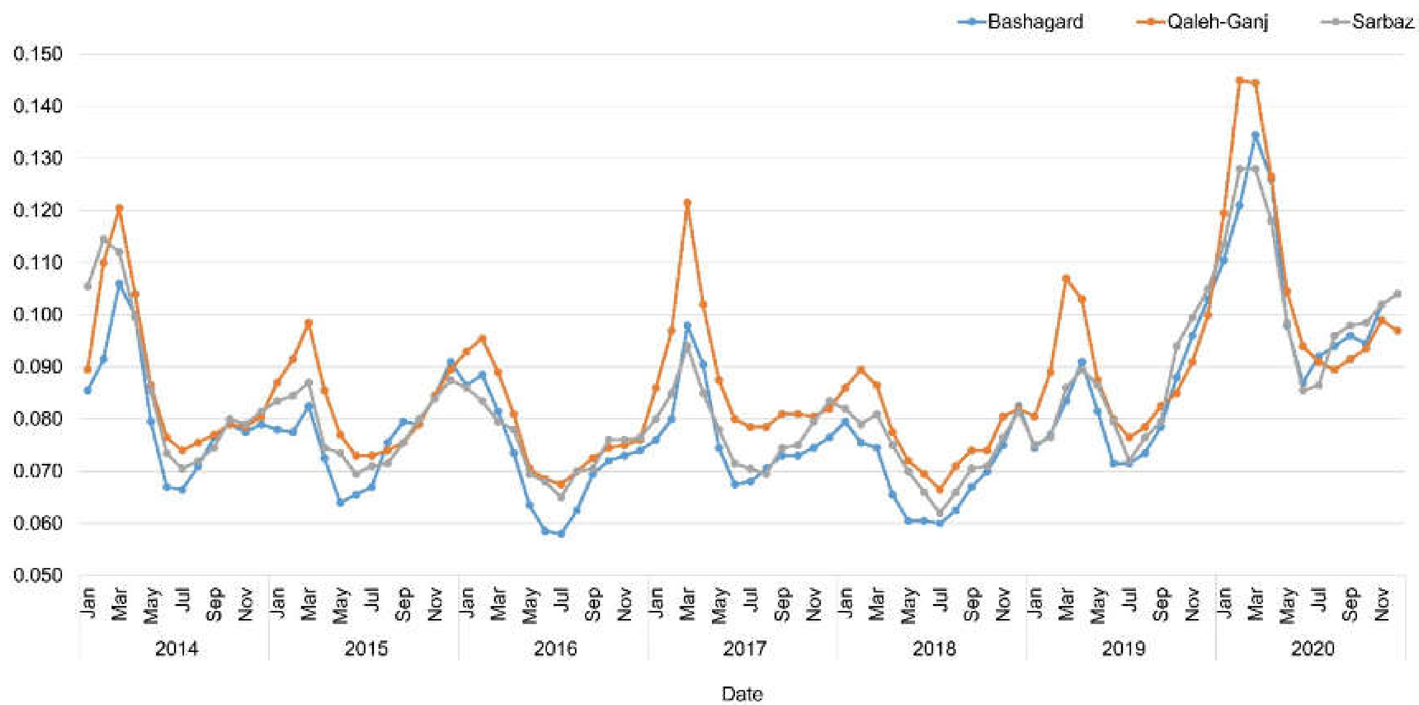


Sample data from Qaleh-Ganj County (Red Boundary) acquired in April 2020. (a) RGB true color; (b) ET; (c) Precipitation; (d) SSM; (e) SUSM; (f) NDVI; (g) LST.

Adaptive LST



NDVI



Bashagard
Qaleh-Ganj
Sarbaz
0.150
0.140
0.130
0.120
0.110
0.100
0.090
0.080
0.070
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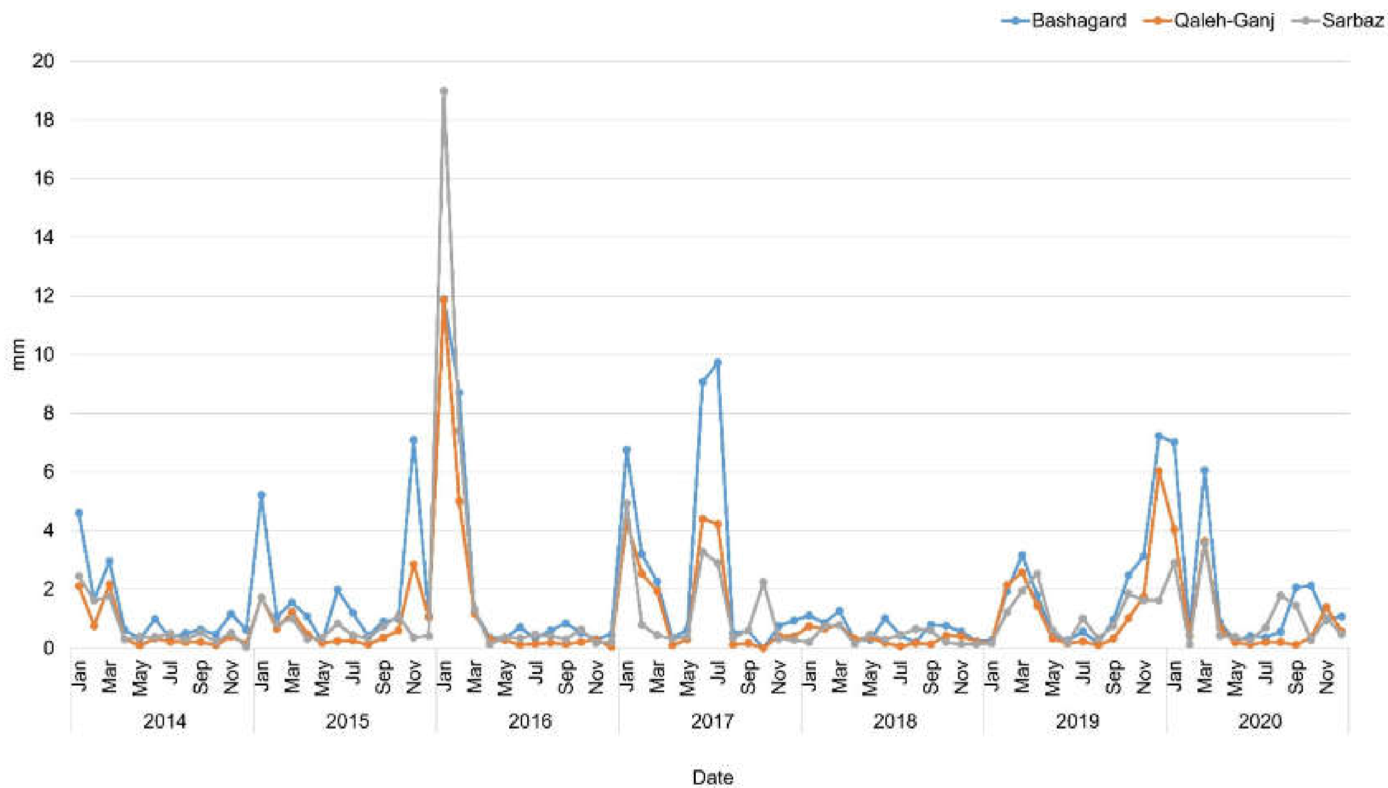
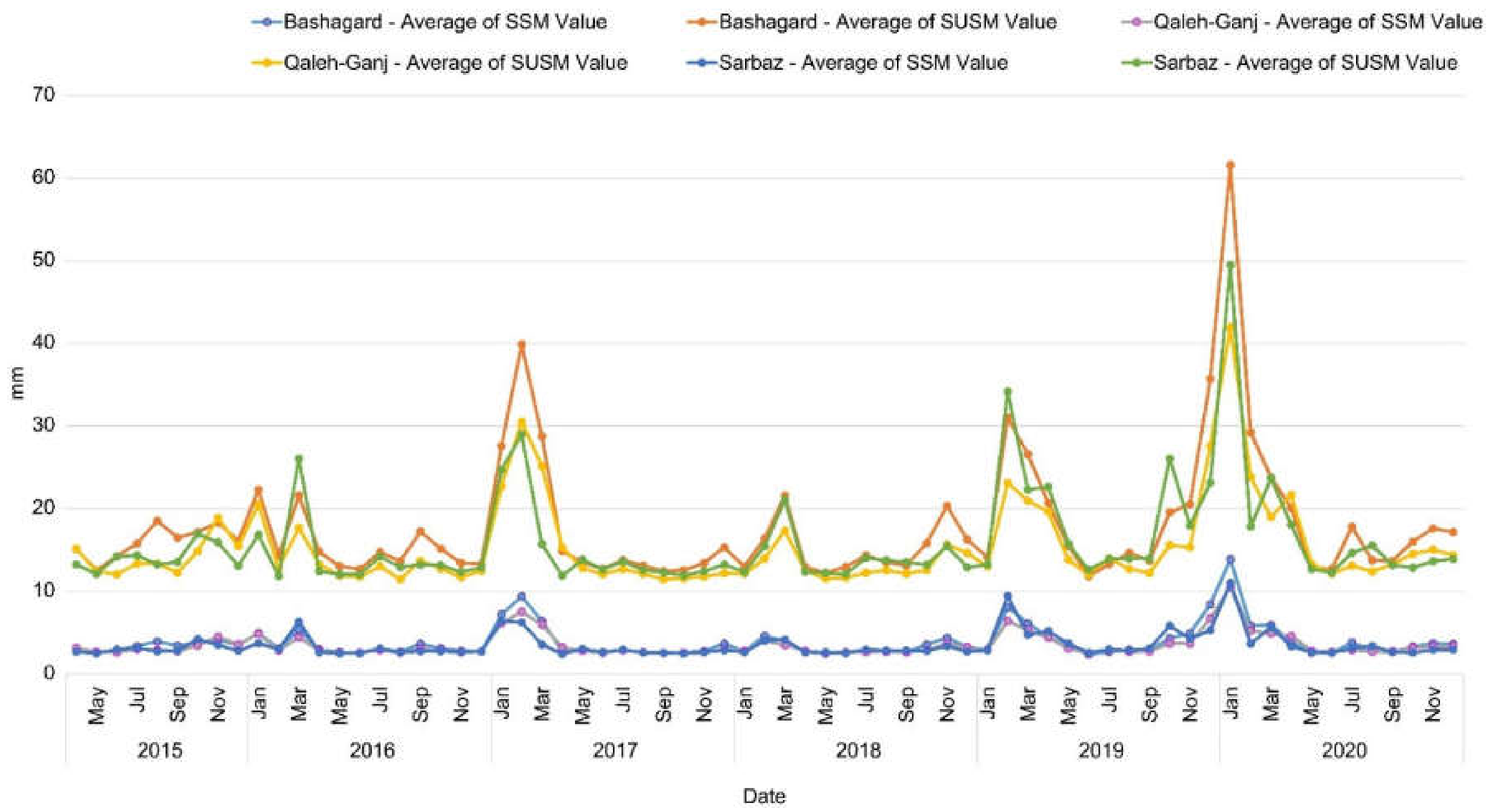
0.050
Jan
Mar
May
Jul
Sep
Nov
2014
2015
2016
2017
2018
2019
2020
Date

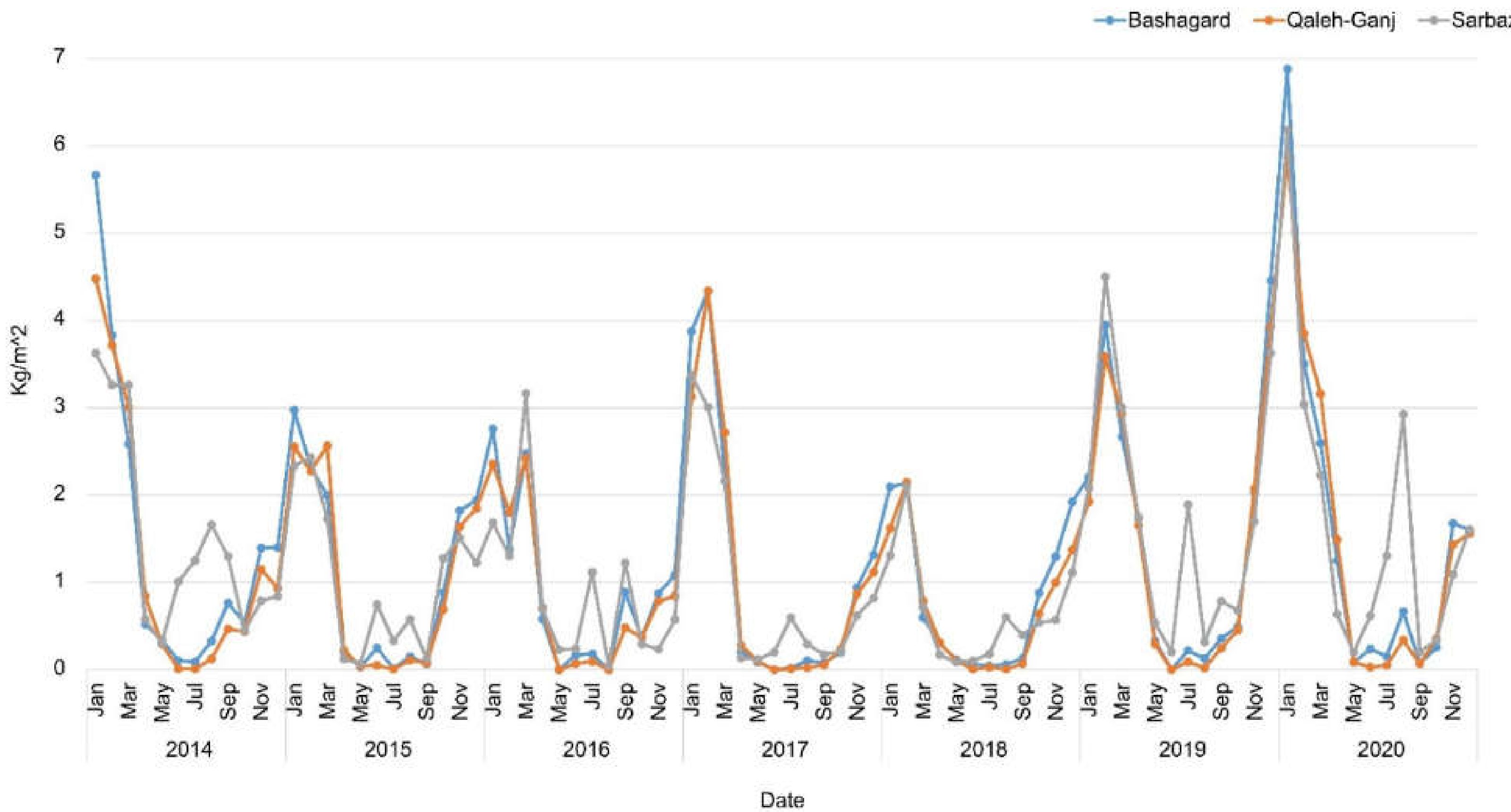
Precipitation



Soil Moisture



ET


Bashagard
Qaleh-Ganj
Sarbaz
Kg/m^2
7
6
5
4
3
2
1
0
Jan
Mar
May
Jul
Sep
Nov
2014
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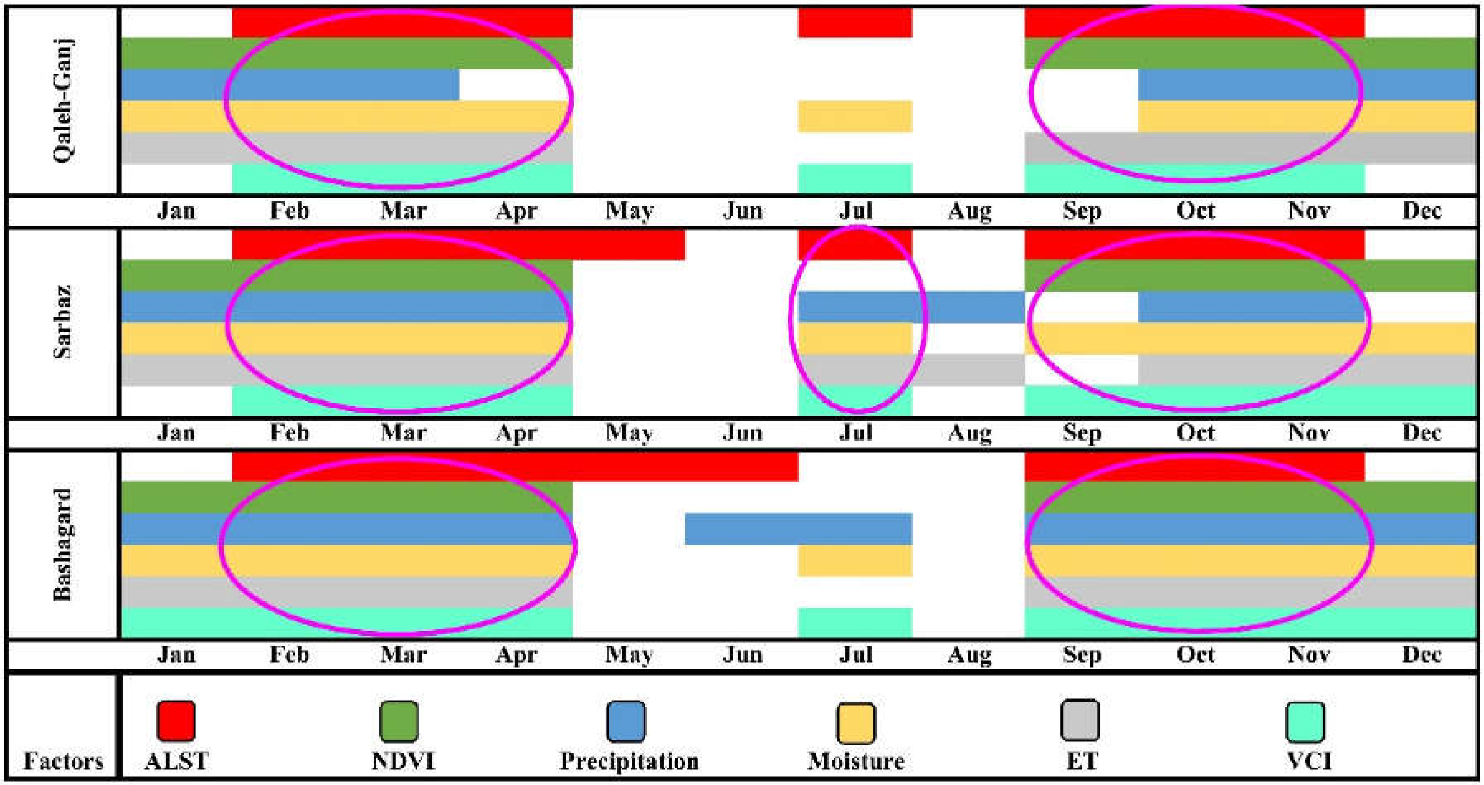
2017
2018
2019
2020
Date

Temporal Prediction



Sample of Spatial Prediction

ELSEVIER

International Journal of Applied Earth Observation and Geoinformation

Volume 108, April 2022, 102746

Predicting the location of larval habitats of *Anopheles* mosquitoes using remote sensing and soil type data

Fahimeh Youssefi [a], Mohammad Javad Valadan Zoej [a], Ahmad Ali Hanafi-Bojd [b, c], Alireza Borahani Dariane [d], Mehdi Khaki [e], Alireza Safdarinezhad [f]

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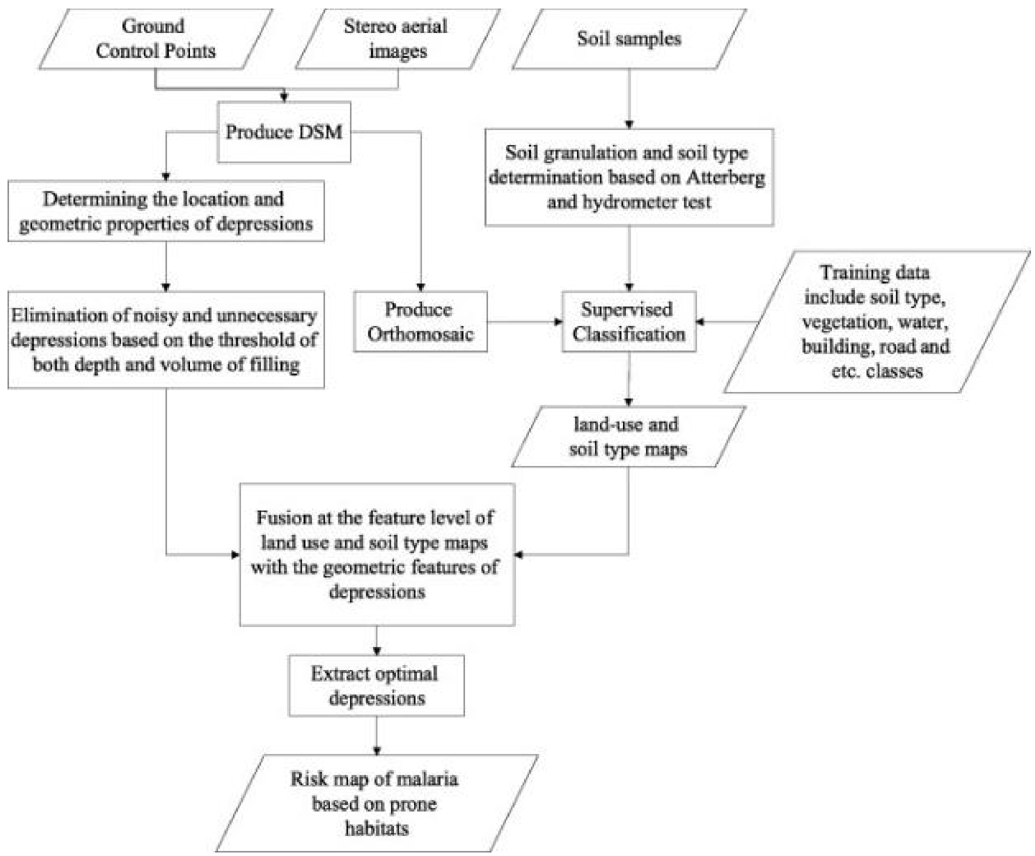
[c] Department of Medical Entomology & Vector Control, School of Public Health, Tehran University of Medical Sciences, Tehran, Iran

[d] Faculty of Civil Engineering, K.N.Toosi University of Technology, Tehran, Iran

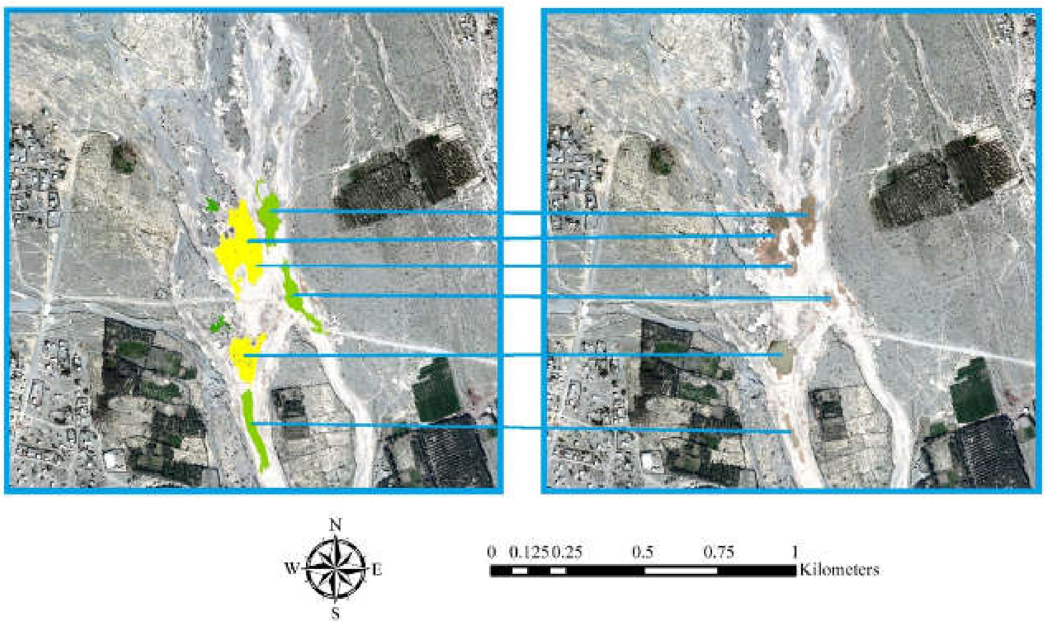
[e] School of Engineering, University of Newcastle, Callaghan, New South Wales, Australia

[f] Department of Geodesy and Surveying Engineering, Tafresh University, Tafresh, Iran

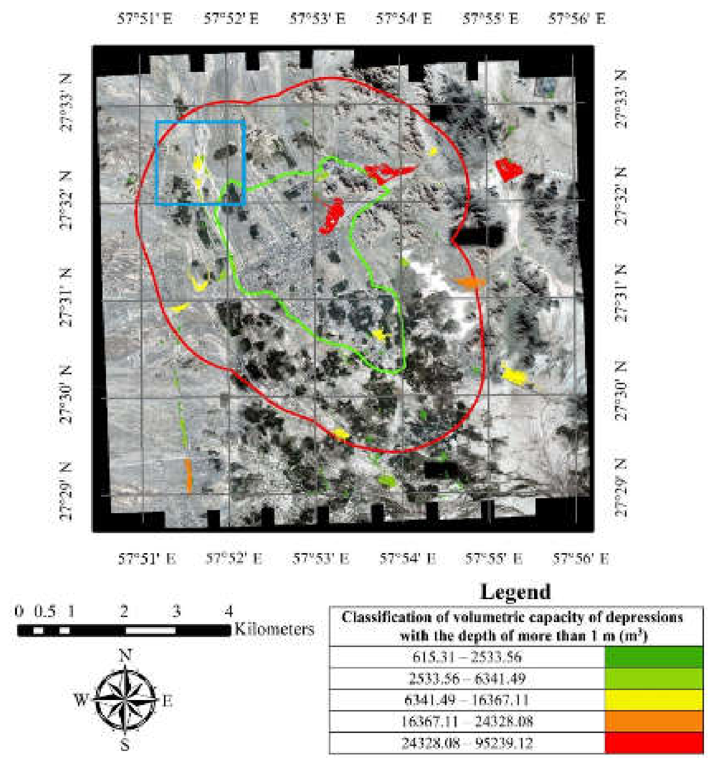
Sample of Spatial Prediction



Sample of Spatial Prediction

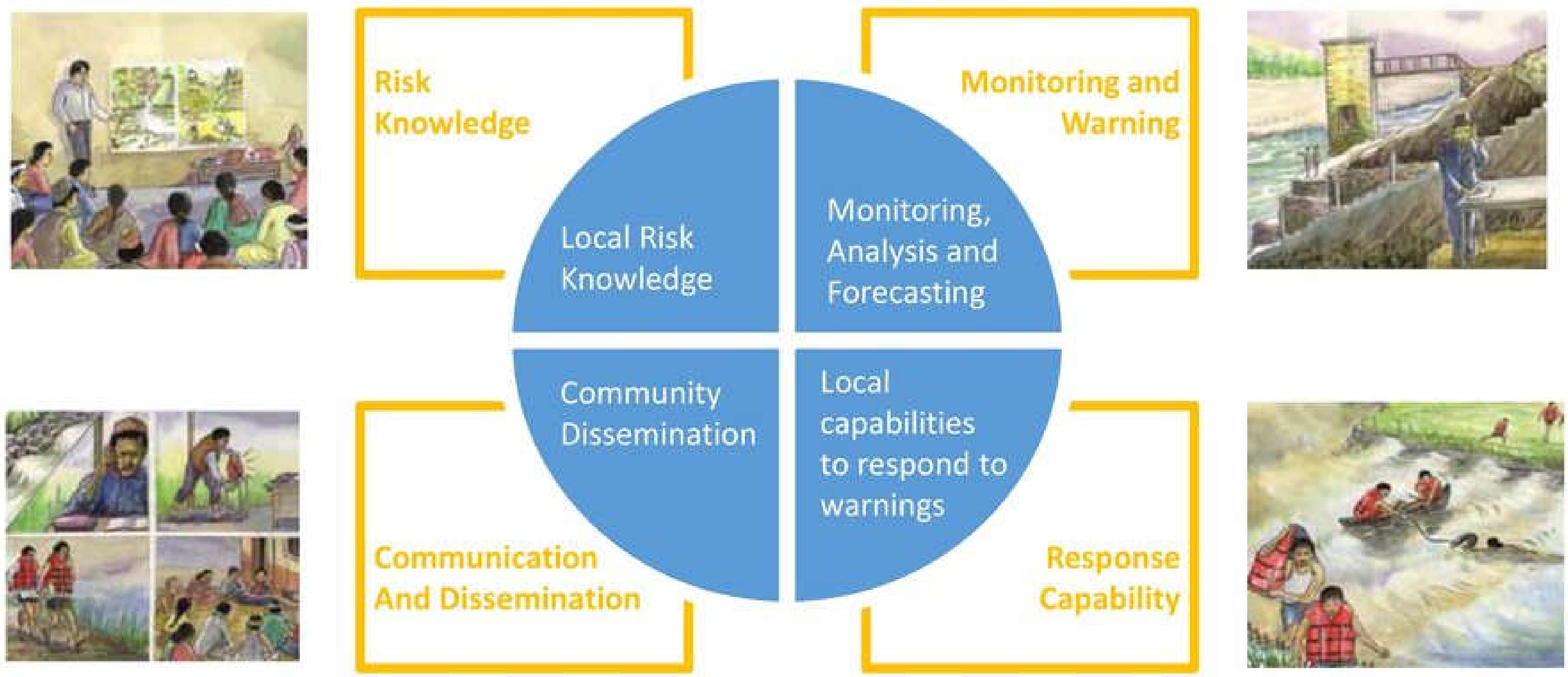


(b)

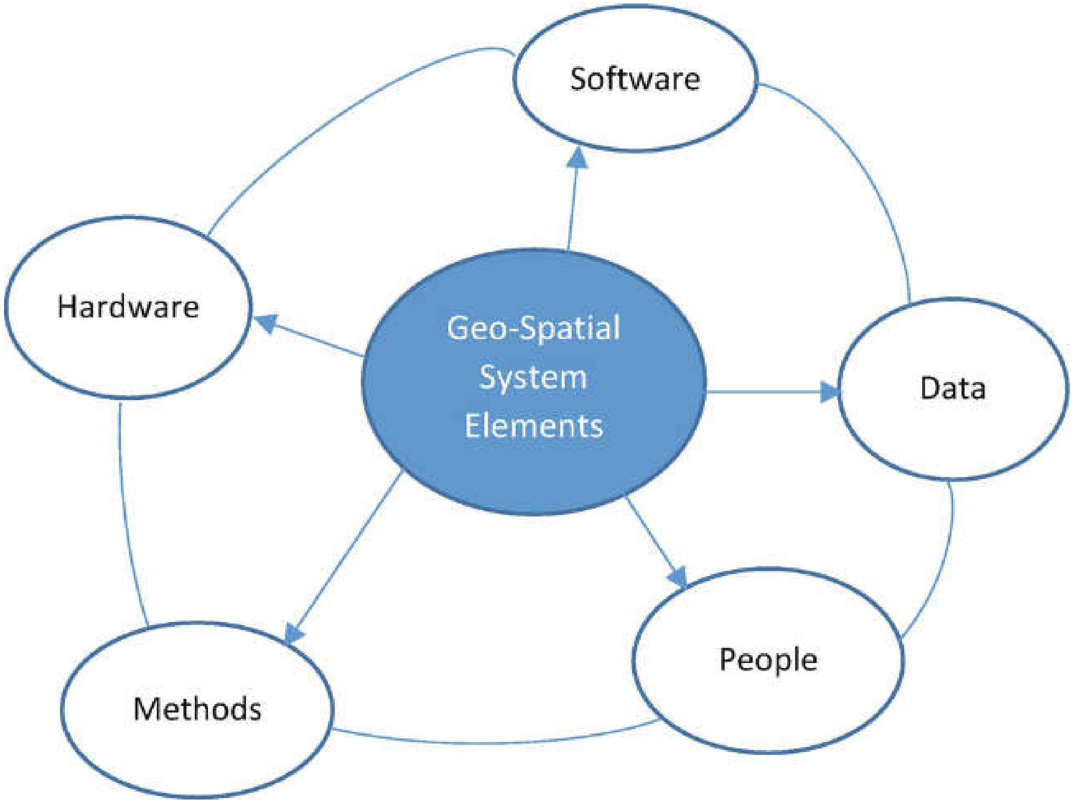


(a)

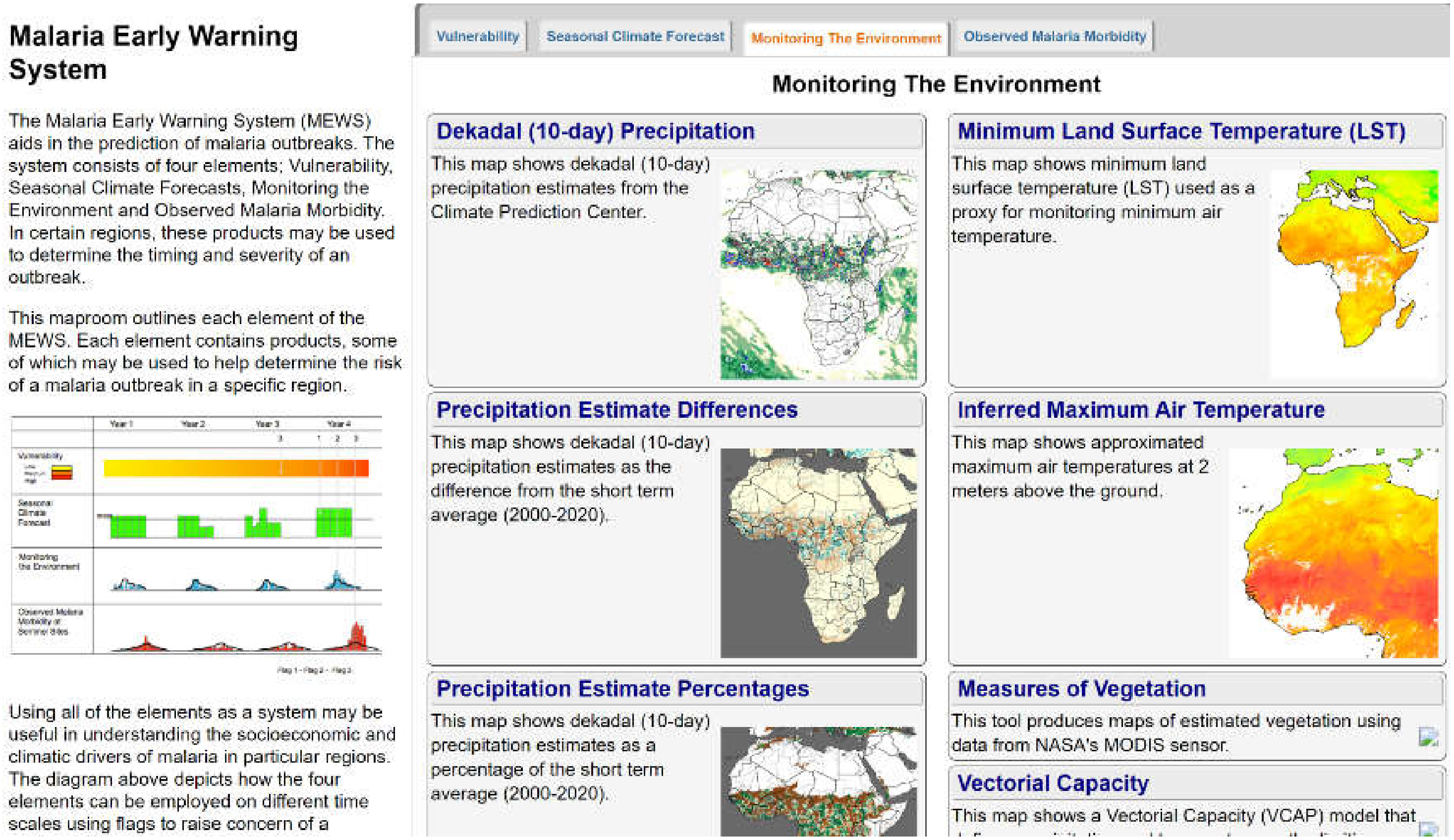
Early Warning System Components



Early Warning System Components



Early Warning System Components



Malaria Early Warning System

The Malaria Early Warning System (MEWS) aids in the prediction of malaria outbreaks. The system consists of four elements; Vulnerability, Seasonal Climate Forecasts, Monitoring the Environment and Observed Malaria Morbidity. In certain regions, these products may be used to determine the timing and severity of an outbreak.

This maproom outlines each element of the MEWS. Each element contains products, some of which may be used to help determine the risk of a malaria outbreak in a specific region.

Using all of the elements as a system may be useful in understanding the socioeconomic and climatic drivers of malaria in particular regions. The diagram above depicts how the four elements can be employed on different time scales using flags to raise concern of a

Vulnerability | Seasonal Climate Forecast | Monitoring The Environment | Observed Malaria Morbidity

Monitoring The Environment

Dekadal (10-day) Precipitation

This map shows dekadal (10-day) precipitation estimates from the Climate Prediction Center.

Minimum Land Surface Temperature (LST)

This map shows minimum land surface temperature (LST) used as a proxy for monitoring minimum air temperature.

Precipitation Estimate Differences

This map shows dekadal (10-day) precipitation estimates as the difference from the short term average (2000-2020).

Inferred Maximum Air Temperature

This map shows approximated maximum air temperatures at 2 meters above the ground.

Precipitation Estimate Percentages

This map shows dekadal (10-day) precipitation estimates as a percentage of the short term average (2000-2020).

Measures of Vegetation

This tool produces maps of estimated vegetation using data from NASA's MODIS sensor.

Vectorial Capacity

This map shows a Vectorial Capacity (VCAP) model that

https://iridl.ldeo.columbia.edu/maproom/Health/Regional/Africa/Malaria/System.html#tabs-3

Thanks a lot for your attention